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Sos Venezuela : an analysis of the anti-Maduro protest movements using Twitter

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Abstract

In this study, we analyze the evolution of the protests after the election of the Venezuelan Constitutional Assembly in 2017. We adopt the idea of a social conflict over diverging opinions about how the world should be. Sharing similar opinion is one basis for a sense of collective identity that facilitates participation in action to bring about desired changes in the world. We approach social conflict as an interaction between different opinion-based groups, in which opinions are formed and transformed leading and supporting different forms of collective action. We analyze Twitter conversations before, during, and after the events of the summer 2017 anti-regime protests in Venezuela. Correspondence and cluster analysis of a corpus of 60,036 tweets is used to investigate the theme and opinions from July to September 2017. Results show that opinions become more extreme and one-sided in response to overt repression and the authority's lack of negotiation with movements. After the repression of the protests and President Maduro's successful implementation of an elected Constitutional Assembly, tweets supporting the rule of law and democratic procedures dissipated, while more radical positions strengthened. These finding suggests that democratic principles rest on a precarious relationship between the individual and the authority. Protest movements may arrive at the paradoxical position in which radicalization is the most straightforward response to repression: The most radical positions survive, while the moderate ones are co-opted or suppressed by the regime. We argue that this dynamic may have potentially negative consequences for democracy and social change.

Keywords: social media; Venezuela; opinions; polarization; radicalization.

SOS Venezuela: An Analysis of the Anti-Maduro Protest Movements Using Twitter

Since 2014 Venezuela has been facing a series of mass protests against the government, which have often been characterized by violent clashes between opposing forces. The scale of these protests increased spectacularly in 2016 and 2017 placing the government of President Nicolas Maduro in a precarious position. Although over 6,000 street demonstrations took place during 2017 with millions of participants, the protests rapidly deflated by the end of August (OVCS, 2017). It is important to note at the outset that the almost immediate demobilization of the protest movement occurred in response to increasingly repressive tactics by the government. That is, the protesters did not stop protesting because they had achieved their aims, but in the face of a setback. The rapid rise and spectacular decline of this movement make it a particular interesting case to investigate the evolution of shared opinions underlying collective action. In this paper, we seek to investigate opinion polarization and opinion radicalization in the context of violent clashes between protesters and authorities. We analyse Twitter conversation to show that concurrently to (and possibly consequently from) the lack of change in the authority's position vis-à-vis the protesters' claims, collective action discourses clustered over more radical arguments. We argue that this dynamic may increase group radicalisation and have potentially negative consequences for democracy and social change.

The Venezuelan events can be understood as an instance of rapid political polarization (Iyengar & Westwood, 2015) analogous to that recently observed in the UK and US (Inglehart & Norris, 2016). Different from the US and UK cases, the Venezuelan events not only involved a significant conflict playing out in online social media, such as Twitter, but also on the streets in increasingly radicalized and violent ways. We analyse the online expression of this conflict by applying recent theorizing in psychology and political science. Specifically, we adopt the idea of a

social conflict based around ideological divisions (Kriesi, 2012) or, in social psychological terms, featuring groups defined by opinions about how the world should be (i.e., opinion-based groups; McGarty, Bliuc, Thomas, & Bongiorno, 2009; Smith, Thomas, & McGarty, 2015).

To explore these dynamics, we analysed the transformation over time of Twitter conversations collected before, during, and after the critical events during the summer 2017 anti-regime protests in Venezuela. We used a data mining approach by performing an automated content analysis of Twitter texts. In particular, we applied correspondence analysis in combination to cluster and sentiment analysis to extract relevant topics, and structural change analysis to investigate change over time.

Opinion-based Group and Political Polarization

Social psychological explanations of political activism have shown that identifying as a member of a group makes protest participation more likely (e.g. Drury & Reicher, 2000; Klandermans, Sabucedo, Rodriguez, & De Weerd, 2002; Simon & Klandermans, 2001). Expanding this line of research, McGarty and colleagues (Bliuc, McGarty, Reynolds, & Muntele, 2007; McGarty, Bliuc, Thomas, & Bongiorno, 2009) have argued that participation and opinion are tightly linked together. In other words, members of activist groups tend to share norms, values and world-views that converge in similar opinions. On the other hand, they have also argued that sharing opinion creates a sense of collective identity and therefore facilitates participation. In other words, opinion-based groups can be understood as one initiator of collective action. They are a form of collective identity that can sit between broad social categories (e.g., nations, religions, and ethnicities) and activist groups.

Opinion-based groups are therefore particularly relevant to understand the political effectiveness of collective action and social movements. Some scholars have indeed argued that the effect of collective action on political change is mainly indirect and it is made possible only through

changes in public opinion, party support, and pressure groups (Giugni, 2007; Olzak & Soule, 2009; Rucht, 2004). In particular, for those movements that are disconnected from institutional actors, getting the attention of mass media and the support of public opinion is a major mechanism to produce change. The role of the so-called silent population is pivotal for supporting or rejecting a protest action seeking social change (Giugni, 1999; Mugny, 1982; Passini & Morselli, 2013). Shaping public opinion is therefore a key element for the success of social movements (Burstein & Linton, 2002; Selvanathan & Lickel, 2018; Soule & Olzak, 2004) and the main goal of collective action is to engage and shape opinions in the general public (e.g., Blee & McDowell, 2012; McCarthy & McPhail, 2006; Snow, Rochford Jr, Worden, & Benford, 1986). Opinion-based groups can be understood as the way through which public opinion supports and feeds protest.

One important aspect of this approach is that opinions are not fixed, they constantly evolve and change. Passini and Morselli (2013) have argued that the negotiation between protesters, authorities and the population, shape opinions and the way these are integrated and manifested into social change. Protesters may embrace more radical forms of political engagement and action in response to a failure of the authority (i.e., the government) to answer their demands (Simon, 2010). In addition, this is more likely to occur where there is a context of great grievances and discontent and strong intergroup division (Kriesi, 2012). Hence, in a context in which the authority not only fails to protect citizens from the grievance, but also uses repression to sedate discontent and dissents, we can expect opinions to polarize and eventually radicalize. Klandermans (2014) has observed indeed that when the politicization of collective identity takes place, the social environment changes into allies and opponents, or, in Tajfel and Turner's (1986) terms, "us" vs. "them." In the process of polarization, the movement-countermovement dynamics may indeed evolve into a sharp distinction

in which each group asserts that what they stand for is threatened by the other group, supporting a radicalization of the intragroup position and intergroup relationships (Klandermans, 2014).

This process is reflected in and possibly initiated by the change of opinion and its position. Although different research traditions conceptualize opinions in contrasting ways (Price, 2007), we define opinions as representations about a subject that is composed of two components: its content (what it is about) and the position that it expresses (a judgement of the content). Whereas opinion polarization refers here to the divergence between positions regarding a certain topic, we define opinions as radicalized when their content directly refers to beliefs, feelings and behaviors that justify intergroup violence and demand sacrifice in defence of one's own group (McCauley & Moskalenko, 2008). Radicalization thus goes hand in hand with the exclusion and annihilation of the opposite position. Radicalization has often been analysed in terms of the progressive extremization of protesters (see Klandermans, 2014). However, it is interesting to consider that radicalization, as a consequence of political polarization, is very much a two-sided process. It does not involve the appearance of opposite opinions within one group but rather it is inserted into an intergroup context in which opinions diverge in a zero-sum manner between groups. Opinion polarization is thus close to those the dynamics that foster intergroup conflicts, such as in-group favouritism and out-group derogation (Hewstone, Rubin, & Willis, 2002) and perception of illegitimacy and identity threat (Livingstone, Spears, Manstead, & Bruder, 2009), on both pro-system and anti-system groups.

Thus, radicalization and polarization represent a danger for democratic social change as it risks of putting the suppression of discordant or dissident opinions at the core of change. The inclusion of multiple viewpoints and the definition of moral and egalitarian norms that are equally good for the different social actors involved in the process of social change are indeed essential to achieve a democratic change (Habermas, 1990). at pOn the contrary, in a polarized context actors are often

judged on the basis of group membership rather than on the content of their claims. In line with Passini and Morselli (2013), polarization is more likely when either the protesters or the authority actively (through delegitimization) or passively (through indifference) shut the door on negotiation, shifting the arguments from the content of the claims to the legitimacy of the actors.

To study these dynamics, we have focused on the 2017 anti-regime protests in Venezuela and the online discussions that took place around democracy and its principles at that time. In particular, we used Twitter data to explore how opinions changed during the protest period. First, we were interested in observing whether polarized and radical opinions emerged in the online discourses about democracy and democratic rights. Secondly, following Passini and Morselli (2013) and Simon (2010), who suggest harsh responses from authorities facilitate polarization and radicalization, we investigated the co-occurrence of the development of these opinions and government decisions and repression.

The Venezuelan Twitter Study

In 2014, a period of mass protests and political demonstrations began in Venezuela initially in response to high levels of inflation and frequent shortages of basic goods (Robins-Early, 2017). Following the suspension of the referendum for a new election to replace President Nicolas Maduro the scale of the demonstrations increased with over a million participants in each of September and October 2016.

These demonstrations continued in 2017, especially after the Venezuelan constitutional crisis of March 29 when the Supreme Tribunal of Justice, mainly composed of supporters of Maduro, took over the legislative powers of the National Assembly (dominated by the Democratic Unity Roundtable – Mesa de la Unidad Democrática – an opposition coalition), and restricted the immunity of its members from prosecution (Casey & Torres, 2017). On May 1, following a month of

protests that resulted in violent clashes and 34 deaths, Maduro called for a constituent assembly in order to draft a new constitution. The waves of protest increased while a popular movement led by the opposition held a symbolic referendum against Maduro's plan for a new constitution on July 16. In a climate of high tension, about 36% percent of the 19.5 million registered voters participated in the symbolic vote, expressing a plebiscitary rejection of the constituent assembly proposed by Maduro (BBC, 2017).

Despite one third of the population actively opposing the Government's plans, the Constituent Assembly elections were held on July 30 and the assembly was officially sworn in on August 4. That is, rather than compromising or modifying its position in the face of mass opposition, the government stuck to its plans, refused to negotiate, and doubled down on efforts to break the opposition. The international community negatively reacted to these events, and several countries refused to recognize this new assembly, as its members were mainly selected from social organizations loyal to Maduro, giving him power over all political institutions (Brodzinsky & Boffey, 2017).

The lack of negotiation between the social movements and the government, and the consequent establishment of the Constituent Assembly represented a turning point in the Venezuelan protest. In the following months, participation in protest marches dropped compared to the period before, as many Venezuelans stated that they had left the protest movements chiefly due to fears of state repression (Lapatilla, 2017). The period from 2014 to 2017 was marked by many violent clashes between protesters and government forces, resulting in more than 10,000 arrests and 219 deaths (including both supporters and opponents of the government). All these events favoured the emergence of two starkly opposing opinions in Venezuela. On the one hand, the pro-government

position considered protesters to be violent and destabilizing. On the other hand, the protesters judged the government to be repressive and dictatorial.

Similarly to the Arab Spring (2010-2012), the Venezuelan protests have been characterized by an intensive use of online technologies, in particular social media such as Twitter and Facebook (Wilson, 2014). The process of opinion polarization and eventual radicalization is quite common in online mediated discussions. Indeed, if online technologies have the relevant advantage of enabling people to express and share their dissent and organizing protests in repressive and authoritarian contexts (McGarty, Thomas, Lala, Smith, & Bliuc, 2014; Tufekci, 2017), they facilitate the formation of distinct and often incompatible and non-communicating factions. This characteristic of social media is particularly relevant for the study of opinion-based groups. Although there is no consensus about the use of social media as a proxy for public opinion, it is undoubted that they represent a powerful tool of opinion construction and communication that has an impact on offline social change dynamics (e.g, Gorodnichenko et al., 2018). Social media is now part of the context against which protest takes place and merits analysis and merely undertaking such analyses is not to assume that social media content authentically captures the views of individuals or that it is representative of popular opinion.

The expanding use of social media in the context of protest and activism (see McGarty et al., 2014; Passini, 2012; Tufekci, 2017), makes Twitter a powerful data source to analyse the development of opinions about democracy and dissidence. Gibson and Cantijoch (2013) argue that social media represent a form of political engagement when used by citizens to communicate or express political ideas. Rojas and Puig-i-Abril (2009) refer to it as "expressive political participation", which entails public expression of political opinions. This form of investment is easily accessible and therefore more widespread than other types of engagement. In this sense, social

media are particularly relevant for the study of opinion-based groups, as they capture how shared opinions, that frame more direct and active political participation, take place and change over time (Conway, 1991).

Among the various social media, Twitter has played a major role in the context of the Venezuelan protest. The penetration rate of Twitter was 28% in a population of about 32 million (Statista, 2018). Thus, although Twitter users in Venezuela might not be representative of the whole population, the use of this platform was quite widespread. Both opponents and supporters of the government used this platform to document and express opinions. They tweeted to mobilize the protest, as well as to directly addressed international organizations and draw the attention on the protests. The idea here is to consider Twitter as a site of contestation where both sides believe they can reach third parties. Even though an individual tweet would probably only be read by a small number of users, each tweet had the *potential* to reach one third of the Venezuelan population.

Method

Data Collection

The R package twitteR (Gentry, 2015) was used to collect tweets in Spanish that mentioned the keyword "Venezuela" combined with (Spanish words) for either "democracy," "freedom," "opposition," "dissident," or "dissidence," from the June 1 to September 4, 2017 (a list of collected search terms and hashtags in Spanish is reported in the Supplemental online material Table A). The time lapse covered the events connected to the reform of the Venezuelan constitution, including the symbolic vote of opposition in July, the consequent protests and clashes between protester and the government forces, the government's decision of ignoring protestations and go ahead with the election of a Constituent Assembly between the end of July and August, and the immediate period

following the establishment of the Constituent Assembly. During this time, the search keywords we used were highly politicized, as they were relevant to the contingent events (i.e., Maduro's authoritarian use of the democratic rule) but also reflected general concepts of how the political structure should be (Morselli & Passini, 2011).

The Twitter Search API was used to collect tweets weekly from June to September[1]. The algorithm collected a corpus of 64,923 unique tweets by 24,911 users and retweeted 266,545 times. In this study, we were mainly interested in investigating opinion development across time, that is how discourses are framed and change around some topics, and less in the influence or share of such opinions among the Twitter community. Hence, we performed content analysis only on unique tweets and not retweets, as the content of retweets does not directly reflect the behavior of the communicator. News tweets, posted by newspapers and news agencies were also excluded. To maximize the pertinence of the tweets with the political situation in Venezuela, tweets in the corpus were either geo-located within the Venezuela GPS coordinates or included the keyword "Venezuela" in the text or user description.

Following Asif and colleagues (2016), hashtags were considered as semantic elements of the text, and included in the analysis. To this purpose, we used regular expressions and customized dictionary to separate composite hashtags into multiple words. Typos were checked and corrected using the Hunspell implementation in R (Ooms, 2017). After text cleaning, the research terms used for the search algorithm and common Spanish stop words (e.g., conjunctions, articles, etc.) were

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1   At the time of the data collection the Search API allowed to collect a selection of tweets in the past 7 days. Where volumes of tweets requesed in a search are large (and determined by the API to exceed a rate limit) , the API returned a sample selection of tweets based on their relevance or popularity. However, because of the quite specific search keywords we used, our tweet collection can be considered reasonably exhaustive. Indeed the rate limit set by the Twitter API (approximately 18,000 tweets) was not hit during any search.

removed and words were converted to their stem using the tm package for R (Meyer, Hornik & Feinerer, 2008).

Analytical Strategy

Content Analysis

To explore the content of the tweets and whether they expressed radical opinions, we analysed the co-occurrence of words in tweets, extracting shared semantic regions via correspondence analysis (CA, using R.TeMiS for R,Bouchet-Valat & Bastin, 2013). Correspondence analysis can be understood as principal component analysis for categorical data. It is used to discover structure in textual data (D'Enza & Greenacre, 2012). CA particularly provides indicators of how the words in a given corpus are associated one another. When using a bag-of-words approach, the words are projected on a factorial space such that the proximity between words indicates a higher association. In linguistic analysis, such proximity can also be understood as shared semantic meaning. The CA calculates the contributions of each word to the inertia of a factorial axis, showing how each word contributes to identifying the axis. Hence, words that are projected further from the centre of the axis provide a higher contribution. The results of the CA were then used to perform a hierarchical cluster analysis with the Ward method to classify the tweets of the corpus into semantic categories that indicate shared topics and indicators of share per day of each topic were constructed to investigate the change over time.

Opinion Position

In order to investigate polarization, a first step is to highlight different and opposing positions (most obviously, those for and against the government). The classification of these positions is not always easily extractable using simple search keywords. However, some specific hashtags about the constituent assembly were more closely related to either pro or against positions. For instance,

#constiutuyenteEsMuerte ("the constituent assembly is death") was used to express a position against it, while #constiutuyenteEsVida ("the constituent assembly is life") was used by supporters. Hence, 117 hashtags including the keyword "constiutuyente" were manually classified as expressing either pro ($n = 40$) and anti ($n = 77$) positions (see Supplemental online material Table A). These hashtags represented only 1.3% of the total hashtags used in the corpus and they did not exhaustively cover every position expressed in the tweets. In addition, sometimes Twitter users engaged in hashtag "hijacking", where hashtags were adopted to mock or criticize the hashtag's sentiment (Jackson & Foucault Welles, 2015).

We collected a complementary corpus of 3,994 tweets (25.7% pro-assembly) mentioning these hashtags. This corpus was split into train (60% of the corpus) and test datasets (40%) to estimate a series of machine learning models to classify the pro- and anti-government positions. The goal was to define a procedure to classify the tweets for which the pro- or anti-government position was unknown. We used a Naive Bayes (NB) classifier estimated via the klaR package (Weihs, Ligges, Luebke, & Raabe, 2005), a decision tree model using the C5.0 method (Kuhn & Quinlan, 2018), a k-Nearest Neighbors (k-NN) as implemented in the class package (Venables & Ripley, 2002), and the linear and polynomial support-vector machines (SVM) in the kernlab package (Karatzoglou, Smola, Hornik, & Zeileis, 2004). Infrequent words and those with near-zero variance were removed from the bag of words. All models were assessed using 10-folds repeated cross-validation, and several tuning parameters. The largest value of accuracy was used to select the optimal model.

All models fitted the data well: the accuracy (best value = 1.0) ranged from .82 to .85; the kappa (best value = 1.0) ranged from .61 to .67. The misclassification ranged from 15% to 18%, meaning that in at least 82% of the cases the models correctly estimated the pro- against-government position of the tweet. Similarly, the area under the curve (AUC), a general measure of classifier

performance for which scores >.50 indicate that the correct classification is significantly above chance level, confirmed the fit of the model. AUC ranged from .88 to .90. Detailed results are reported in the supplemental online material, Table B. Each of these models was considered as an independent classifier and tweets were attributed a pro- or anti-government position on the agreement of four out of five classifiers. Tweets for which two or more models did not produce the same result were considered as "uncertain classification."

Once each tweet was assigned to a specific position, we measured opinion polarization as the absence of co-occurrence of different positions within an opinion, that is the difference in the standardized distribution of each position. A difference of 1 indicates that the two distributions differ by one standard deviation, hence larger values indicate higher polarization. Of course, the simple co-occurrence of two positions is no guarantee that a certain topic is discussed and judged with the same valence. As a way of providing a tighter focus on the content of each position, we applied a dictionary-based word count analysis of the corpus (Tausczik & Pennebaker, 2010) with the quanteda package for R (Benoit et al., 2018)[2]. The analysis searches the text for words or word stems that have been classified into categories defined a priori. All Spanish words appearing more than twice in the corpus were judged for their fit to seven categories that are relevant to the study of collective action: collective action; efficacy and coping; violence and radical actions; political action and democracy; law enforcement; extremism; and illegitimacy (for a similar approach see Smith, McGarty, & Thomas, 2018). These categories are shown in the Supplemental online material Table C. The words were classified by one author and checked by a second. The second judge agreed with 98.2% of the classifications. The six instances of disagreement were resolved by discussion. The analysis shows the average percentage of words per tweet relative to each category.

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2   This analysis is equivalent to the more commonly used Linguistic Inquiry Word Count (LIWC: Pennebaker, Boyd, Jordan & Blackburn, 2015) software. Results from the two packages are indeed identical.

Building on Habermas' (1990) idea that multiple viewpoints are essential to the concept of democracy, we considered a particular opinion as polarized when it was shared and discussed mostly by one side (i.e., absence of polyphony) and it referred to very different collective action categories (i.e., different valence attached to content of that topic).

Longitudinal analysis

Finally, to investigate how opinions developed over time and to relate their change to historical events, we transformed the clusters into time series which indicated the distribution of each shared topic across time and the position within each topic. When analyzing overall trends we focused on the distribution per day to have a fine-grained indicator of opinion change and relate it to contextual events (e.g., Government response). When focusing on subgroups (i.e. positions), we aggregated the data by the week to overcome problems linked to the small sample size of pro-government tweets.

Drawing on Passini and Morselli's (2013) model, according to which opinions are changed by the interplay between protesters and the authority, we highlighted six key events that depict such interplay: the date of the symbolic vote held by the opposition against the change of constitution (July 16); the violent clashes between protest and police in the following days leading to the general strike (July 20); the constituent assembly election day (July 30), in which 10 individuals died in violent clashes; the constituent assembly formation (August 4) and following intervention of the police to disperse protesters and barricades. The date of these events mark, on the one side, the progression of the protest (i.e., the symbolic vote, the general strike) and the response of the authority on the other. These events were then contrasted to the progression of opinions across time.

We performed structural change analysis (R package strucchange, Zeileis, Kleiber, Krämer, & Hornik, 2003) to test whether the distribution and the positions of the tweet changed across time and when such changes happened. Structural change analysis is a model-based technique to determine

how many inflection points better describe a curve or time series. The best fitting model is assessed via the Bayesian Information Criteria (BIC): The lowest value indicates the best fitting model.

All the analyses were conducted on Spanish text. In order to make them more accessible to the international reader, translated text has been presented in English throughout (see Supplemental online material Table D).

Results

Extracting Shared Topics from the Tweets

The tweets' content was first analyzed using correspondence analysis. Sparsity was set to 99.5% to exclude words that were present only in 0.5% of the tweets, and the data-term matrix was aggregated by the week. The final corpus with 99.5% sparsity included 53,307 tweets and 198 terms. Figure 1 shows the projection of the terms on a factorial space. The first dimension explains 33.5% of the variance and includes on the negative side of the axis terms such as ultimatum (4.4%), regime (24%), coup (1.7%), Organization of American States (OEA, 1.4%), UN (1.3%), and assassin (1.3%). Terms on the positive side are defence (9.2%), resistance (6.2%), legitimate (4.6%), rebellion (3.4%). The second dimension explains 22.1% of the variance and it is characterized on the negative side by terms such as referendum (21%), popular (13.3%), free (5.3%), Leopoldo López (2.5%) which are related to the popular vote mi-July 2017. On the positive side of the axis, there are terms such as (self)-defence (1.3%), terrorist (0.9%), collective (0.9%), Human Rights Watch (0.7%), Bolivarian National Police (0.6%, i.e., Venezuela's national police force and not to be confused with Bolivia's National Police Corps).

The CA results were then run in a hierarchical cluster analysis to highlight different common positions of arguments and opinions. The analysis extracted three different categories of tweets (Figure 1). The first cluster gathered 17,867 tweets around the legitimacy of the constituent

assembly. This category was characterized by tweets about the constituent assembly, the symbolic vote against it in July and the subsequent negation of its legitimacy by the government. It was connected to words such as: fraud, justice, change, free, today, and future; but also: now, yes, let's go, we want, vote. Examples[3] of tweets were "This illegitimate constituent [assembly]destroys democracy. Venezuela asks for liberty and justice and says no to Maduro's narco regime"; "We want to delegitimize the system"; but also "The constituent [assembly] is peace, the Government is peace, Venezuela is peace. The opposition is terrorism," and "The rest of the world will see when the Venezuelan opposition will behead the police like the ISIS does."

The second cluster was named the condemnation topic (n = 29,139), and focuses on what happened during the protests, reflecting on either the repression of the police and the victims or critical statements on the protesters' behavior. It contained names of cities and states in which protest took place, as well as international institutions as United Nations and Human Rights Watch and news network such as CNN. This cluster is also associated with more valenced terms such as dictatorship, terrorist, terrorism, assassin, and regime. Examples of tweets were: "We demand freedom for all non-political and military prisoners who are victims of the dictatorial regime," "We are all victims of torture, we are not allowed freedom to buy food or medicines and they kill and repress us," "In Venezuela there is an invasion of fascist murderers. Either we fight and stop it, or we will lose the country forever." Counter-movement positions were expressed in tweets such as "The world must know that in Venezuela there is no democratic opposition but terrorists who destroy everything in their path," and "In Venezuela there is no political opposition, but a terrorist and fascist one."

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3   We needed to protect users' safety and anonymity but balance that with Twitter's terms of service that require the owners of intellectual property to be identified as authors. Thus all reported examples are adaptations and translations of text rather that are consistent with the original tweets but which do not actually exist in the corpus.

The third cluster groups tweets that express the necessity of street collective action and rebellion, and therefore was named the revolution topic (n = 6,316). It was associated with words such as revolution, rebellion, legitimate, defence, and the main police institutions in Venezuela (Bolivarian National Police, Bolivarian National Guard, Bolivarian Armed Forces). Examples are: "When tyranny is the law, revolution is order" on the one side. "These are not rebels, they are miserable terrorists who seek to destroy democracy in Venezuela. Only criminals support them," on the other.

At the centre of the plot, and equally distant from the three clusters there were terms such as dictatorship, narcos, support, we need, help, urgent. These terms were less discriminating and were shared among the different topics.

Opposite Positions across Topics

To better understand the positions across topics and investigate polarization, we estimated the pro- and anti-government positions of the tweets in the corpus by means of the machine learning procedure described above. The top part of Table 1 shows the distributions inside each topic of the pro and against the [Constituent] Assembly hashtags, while the bottom part shows the estimated position after applying the machine learning procedure. Although in all three topics the majority of tweets were anti-government, some pro-government positions were also expressed. Among the three clusters of tweets, the condemnation topic was the topic with the highest incidence of pro-government tweets. For the remaining two topics, 4% of pro-government tweets were estimated in the [Constituent] Assembly legitimacy topic, and only 2.7% in the revolution topic.

Figure 2 shows the distribution of the two positions across time, standardized by position. Because of the small number of pro-government tweets, data were aggregated by the week. Overall, pro-government tweets were mostly distributed in the first half of the summer, in the days before the

symbolic referendum (July 16) and preceding Maduro's decision to carry on with the election of the constituent assembly. These days were associated with violent clashes between protesters and the authorities. Anti-government, but far fewer pro-government, tweets were also present in the second part of July, in which the National constituent assembly was elected (July 30) and sworn in (August 4). When looking at the different distribution in each topic, it is worth noting that pro- and anti-positions in the condemnation topic followed the same pattern across time. By contrast, higher rates of anti-government tweets were written in the second part of the summer for the legitimacy and the revolution topics. Especially in the latter period, the highest portion of anti-government position was located in the final part of the observed period.

Because of the relatively small number of pro-government tweets in the corpus, these results should be used with caution. Nevertheless, Figure 3 shows that very similar categories were used in both positions to talk about the legitimacy of the constituent assembly. Unsurprisingly the most heavily used categories were illegitimacy, collective action, efficacy and democracy. Tweet conversations in the Condemnation topic differed instead between pro- and anti-government supporters: The former pointing more at extremism and violence (in an accusatory way towards the protesters), while the latter focused on collective action, illegitimacy and democracy. Finally, the Revolution topic was associated with the largest difference in the tweets. These tweets referred more frequently to political action, as well as violence and radical action, than the other two topics. In addition, anti-government tweets on this topic had higher rates of collective action and efficacy related words than all the other positions and topics, while pro-government tweets peaked on law enforcement and violence.

Shared Topics across Time

Concerning change over time in the topics, the top part of Figure 4 shows the change in the total volume of tweets and retweets from June through September. The plot shows a rapid increase of the volume of tweets and retweets about democracy between the end of June and beginning of July 2017. After that period, democracy was less commonly referred to in the tweets, although it remained at higher levels than the beginning of June throughout July and August.

The bottom part of Figure 4 displays instead the distribution of the three clusters in the same period[4]. The plot shows that the condemnation topic was most prevalent during June. Starting from the beginning of July, this topic became less predominant, and the Twitter discussion converged on constituent assembly legitimacy. Condemning and asserting the legitimacy of the vote were therefore the two most common topics during this period, while tweets about insurrection remained more marginal. However, after the Constituent Assembly was elected and the police started dismantling barricade and protests, the revolution topic also became more central.

To test the change of this third topic we used structural change analysis. We tested models with 1-5 changes in the time series of the revolution topic. The best fitting model (i.e., the model with the lowest BIC, see Table 2) was obtained when only one change was specified. The analysis showed that this change occurred on August 11, with a 95% confidence interval going from August 10 to August 13, confirming that the change of topic occurred in the period immediately following the swearing in of the Constituent Assembly (August 4).

Concerning the polarization change across time, we were interested to investigate whether polarization was more salient after a certain time point. Figure 5 shows the difference between the

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4　　　　The Twitter API search algorithm does not return complete data, and the data volume might vary by day. However, if the search parameters are kept constant, any selection bias should itself be randomly distributed (and hence there should be no bias on average). Using the proportions of the clusters by day instead of their raw frequencies is therefore more robust and less sensitive to random variations in the volume, due to the search algorithm.

standardized distribution of pro- and anti-government tweets across time. This result is in line with the previous result showing that polarization increased peaked in two moments: when the opposition had organized the symbolic vote in June 17, and after the failure of obtaining a response from the authority (August 4 and following days). In addition, the levels of polarization of this topic remained higher by the end of August (period after the last peak, $M_{polarization}$= .52), compared to the beginning of the protest in June (period before the first peak, $M_{polarization}$= .19).

Discussion

This study's aim was to investigate the interplay between protest, authority, and politicized opinions expressed on Twitter. We wanted to investigate whether opinions on democracy and democratic rights became more polarized during the development of the street protest and in response to the measures taken by the regime. Our results highlighted how opinions changed across time and how discourses became more polarized in co-occurrence of specific political events.

In the early summer of 2017 the discourses about democracy, opposition and dissidence were mainly dominated by the condemnation topic in which different, sometimes conflictual, viewpoints were present. With the progression of time, fewer tweets referring to democracy were produced around this topic while the use of one-sided discourses in the tweets became more predominant. In particular, a direct call for collective insurrection emerged after August 11. After months of debates, strikes and protests, the Constituent Assembly was elected and sworn in on August 4, notwithstanding international disapproval and active rejection by the opposition, which was made concrete in the symbolic referendum on July 16. As a matter of fact, after the Constituent Assembly was sworn in, the participation in the protest dropped remarkably, and the authorities coordinated to repress and quickly dismantle the remains of the social movement. The protest lost public support

and participation in street protests became thinner, probably as a consequence of frustration and the perceived lack of efficacy of the struggles, and anxiety about repressive tactics.

Our results suggest that, parallel to the loss in both the volume of collected tweets and participation in street protest, polarized positions grew in our sample with the momentum of the debates, inciting revolution and rebellion. In other words, although the Maduro government's actions succeeded in repressing the protest movement, such repression seemed also the fertile ground for extreme, radical positions, as shown by their higher centrality in the social media discussions and the largest difference between positions within the topic. The legitimacy of the Constituent Assembly became a less central issue for Venezuelan democracy, as shown in the progression across time of the pro- and anti-constituent hashtags. Questioning the legitimacy of the whole system assumed stronger emphasis, as did calls for more radical steps, such as violent revolution.

In conceptual terms these results point to the formation and possibly reformation of an oppositional opinion-based group of the form anticipated by Bliuc and others (Bliuc et al., 2007; Smith et al., 2015). As the protests grew there was a concomitant online mobilization around the themes of that protest. As the government crackdown intensified there was a transfer in online sentiment that can be interpreted as the rise of a force that favored revolution. Our results show that parallel, and possibly consequently, to the loss of support to the protest, collective action discourses clustered around more radical arguments. Despite the overall number of tweets decreasing by mid-August, more tweets were collected on the revolution topic in this period than in June and July and the positions within the topic became monophonic. We cannot tell from these Twitter data whether this is a transformation where supporters of largely peaceful protest became supporters of armed rebellion, or whether existing supporters of revolution merely replaced peaceful protesters on Twitter, but it does seem obvious that the transition that is present in these data presages the change

in tactics by Maduro's opponents. At the time of writing in January 2019 the challenge to Maduro remains stark but that challenge has not returned in the form of mass protests on city streets but in a complex set of attempts to replace the Maduro government with support and opposition by foreign governments and the prospect of armed conflict.

We suspect that this change of tactic is due to at least two different factors. The first one is that protest groups became more isolated and were left as the sole actor to contrast the authority actions. According to the Inter-American Commission on Human Rights' report, dissent was already criminalized in Venezuela, and the government used the justice system to repress it. A radicalized rhetoric would thus play into the government's game of isolating the opposition even further. In this case, the protesters' claims would lose the leverage vis-à-vis the authorities and possibly lose efficacy (Giugni, 1999). Alternatively, the loss of mass support for the movement could have encouraged protesters to cluster and agree around more specific arguments. This could facilitate the organization of the broad movement into a more structured and defined steering group, which could act as an entrepreneur of identity (Reicher, Haslam, & Hopkins, 2005) becoming a reference for promoting social change. This type of promotion might not happen necessarily through the current institutional means (e.g., petitions, referendum), especially when the authority does not respond to such means. Reicher and Haslam (2012) have argued that the primary goal of such steering groups is to open the door to the cognitive alternatives, showing a convincing argument that different social and political structures are possible.

Limitations and Strengths

We conclude by reflecting on the limitations and strengths of this research. In this study we showed how Twitter can be analyzed as a site of contestation for studying the change and dynamics of opinions, at relatively small cost. At the moment of writing, Twitter data can be freely obtained

via the company's API and the analyses were performed with open-access and open-source software. However, this is not the sole nor the main advantage of this type of data. We believe social media data have the advantage of being embedded into the reality of the historical and social context, capturing change over time. That being said, it is important to keep in mind what the data represent. In the context of political contentious, the tweets are used as manifestos, to coordinate action, to give public visibility. They are communicative acts that channel meaning, values and positions, amplifying the sense of collective agency (Segerberg & Bennett, 2011; Weller, Bruns, Burgess, Mahrt & Puschmann, 2014). The nature of these data is hence their main advantage and their main disadvantage at the same time. It is an advantage when the research aim is to investigate the expression of positions and opinions, in the framework of opinion-based groups. However, it tells little about the motivations and the reasons behind such positions.

The question as to whether these social media contributions are demobilizing instances of slacktivism, that replace or substitute for offline action (Schumann & Klein, 2015), remains worth asking but our data suggest a wider and deeper role. Social media outrage goes hand-in-hand with offline action, at different times and performing different functions (Odağ, Uluğ, & Solak, 2016; Smith et al., 2015; Thomas et al., 2015). Twitter, by providing anonymous users some perceived protection from reprisals, and the capacity to create hashtags around themes and issues, is ideal for contestation. Unlike Facebook with algorithms that contribute to creating homogeneous echo chambers of political and other opinion (Bakshy, Messing, & Adamic, 2015; del Vicario et al., 2016), Twitter is the ideal platform for those who wish to make it clear that people they disagree with are wrong, and to provide every opportunity to ensure that those people get to see that, but it is also a platform where anonymous users in many countries can call for action from fellow supporters of a cause, even where that action is heavily policed (Fisher, 2016). For this reason, media like

Twitter have been widely used in areas in which the authority repression is high and mainstream media are controlled by the government.

In this paper we have applied machine learning algorithms to changes in opinion and positions that link to the rise and fall of collective action on the street. Pro-governmental positions were relatively rare in our corpus and some analyses, such as the word categorization, used small datasets. Given the absence of statistics on Twitter opinions, we cannot tell with precision whether the low incidence of pro-governmental positions was because those people use Twitter less, or because they tweet less frequently about Venezuelan democracy. Because we were interested in opinions on a relatively narrow aspect, our choice of search terms had an impact on both the content and the users in our corpus. Alternative techniques of search keywords generation could be used to expand the corpus if the research aims at investigating the emergence and relevance of a larger set of opinions. In addition, the unit of analysis of this study was the tweet. Some computational tools have also been developed to estimate users' political positions and adopt a person-centred approach (Barbèra, 2015) and expand this field of research. We believe the temporal dimension of this type of data can help to overcome some of the usual limitations of collective action and social movement research. In particular, it allows for the longitudinal analysis of mass protests otherwise notably difficult to realize as survey administration and protest timings do not easily coincide (Lee, 2002). It also allows for a refined analysis of the time frame of opinion change. To date, opinion research has mainly investigated change across years, mostly because it relied on extended surveys, such as election studies. The use of social media overcome this limitation, providing real-time data and allowing to investigate faster, and sometime more fragile, dynamics in social movements (Tufekci, 2017).

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Table 1. Distribution of pro- and anti-government positions among the topic clusters.

Position using hashtags	Assembly legitimacy Topic	Condemnation topic	Revolution topic
Pro-Assembly	39 (8.7%)	780 (50.6%)	11 (9.7%)
Anti-Assembly	411 (91.3%)	760 (49.4%)	102 (90.3%)
Model-estimated Position			
Pro-government	57 (0.4%)	1341 (3.8%)	39 (0.6%)
Anti-government	14038 (97.x6%)	30534 (86.2%)	6163 (96.5%)
Uncertain			
classification	284 (2.0%)	3547 (10.0%)	187 (2.9%)

Table 2.

Model results of the structural change analysis

n. breakpoints	BIC	Corresponding dates
0	-95.95	-
1	-174.23	11-Aug
2	-167.98	19-Jul; 11-Aug
3	-163.57	17-Jun; 17-Jul; 11-Aug
4	-155.65	17-Jun; 04-Jul; 19-Jul; 11-Aug
5	-143.26	17-Jun; 02-Jul; 16-Jul; 30-Jul; 13-Aug

Figure 1. Graphical representation of the correspondence analysis
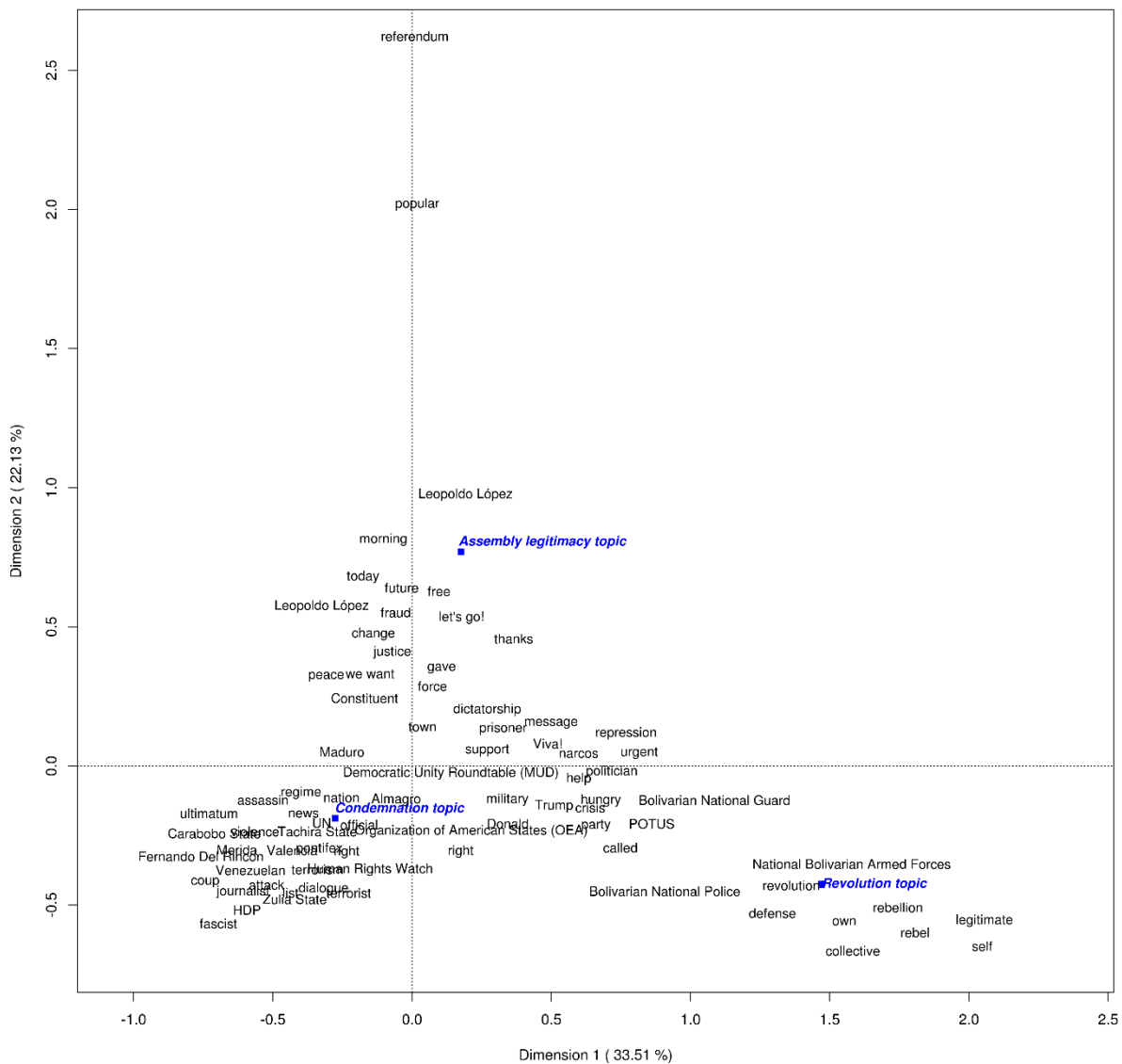
Note. Only the 80 most frequent words are plotted

Figure 2. Distribution pro- or anti-government tweets across time.

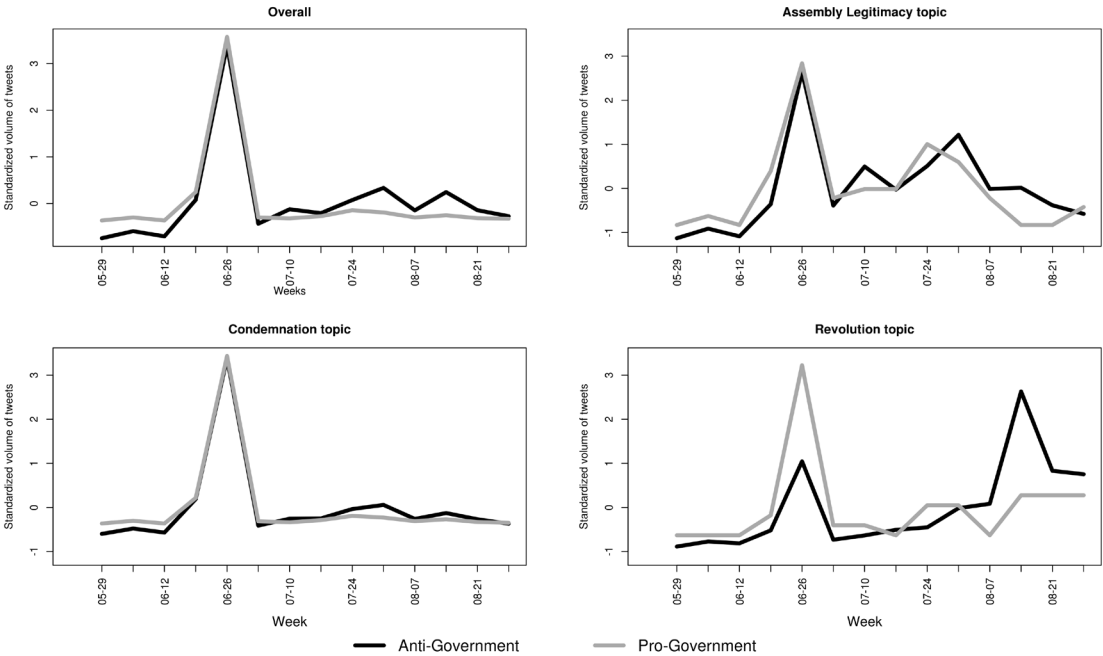*Note.* Dates are shown in the form Month-Day (so 06-01 is June 1st)

Figure 3. Average prevalence of each category by topic and position
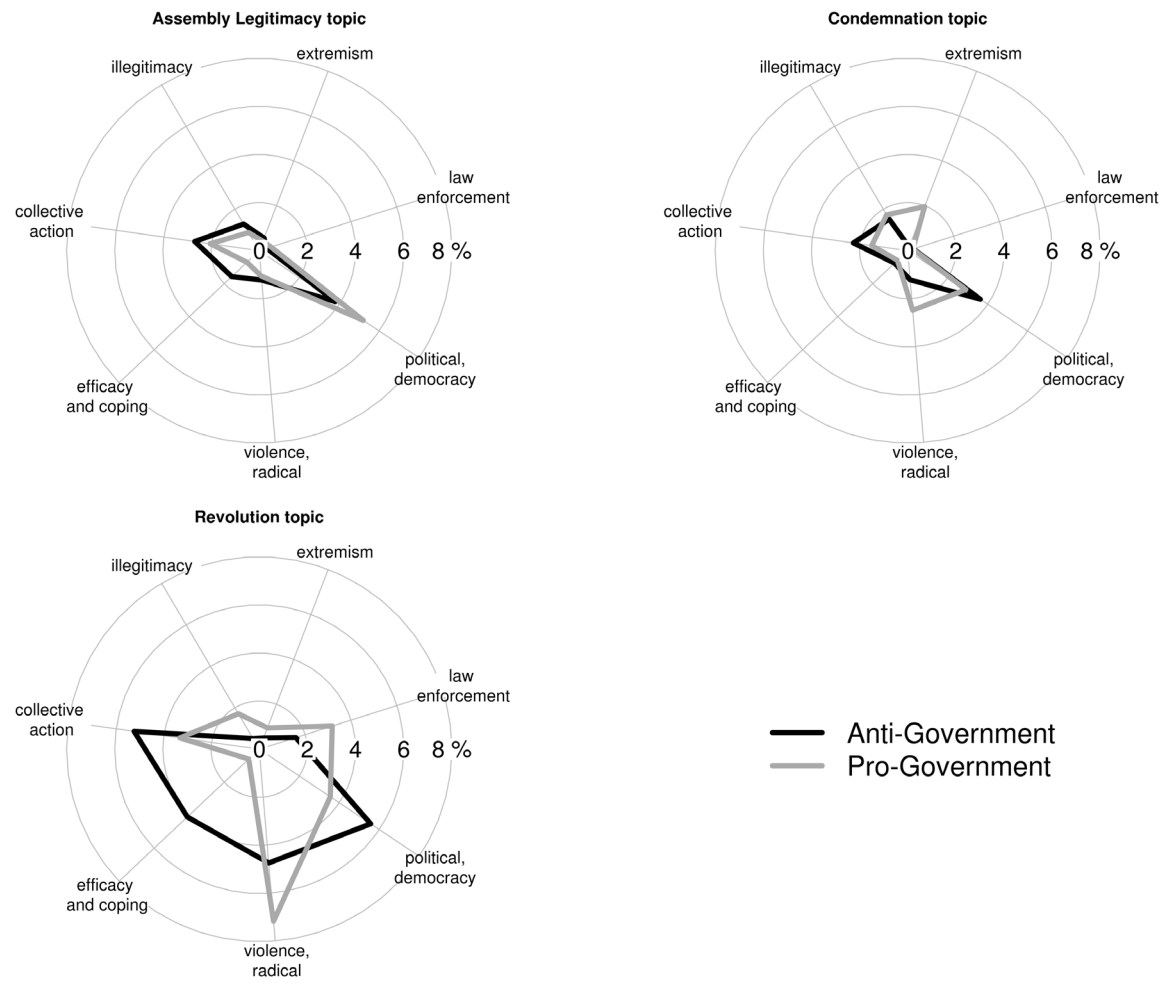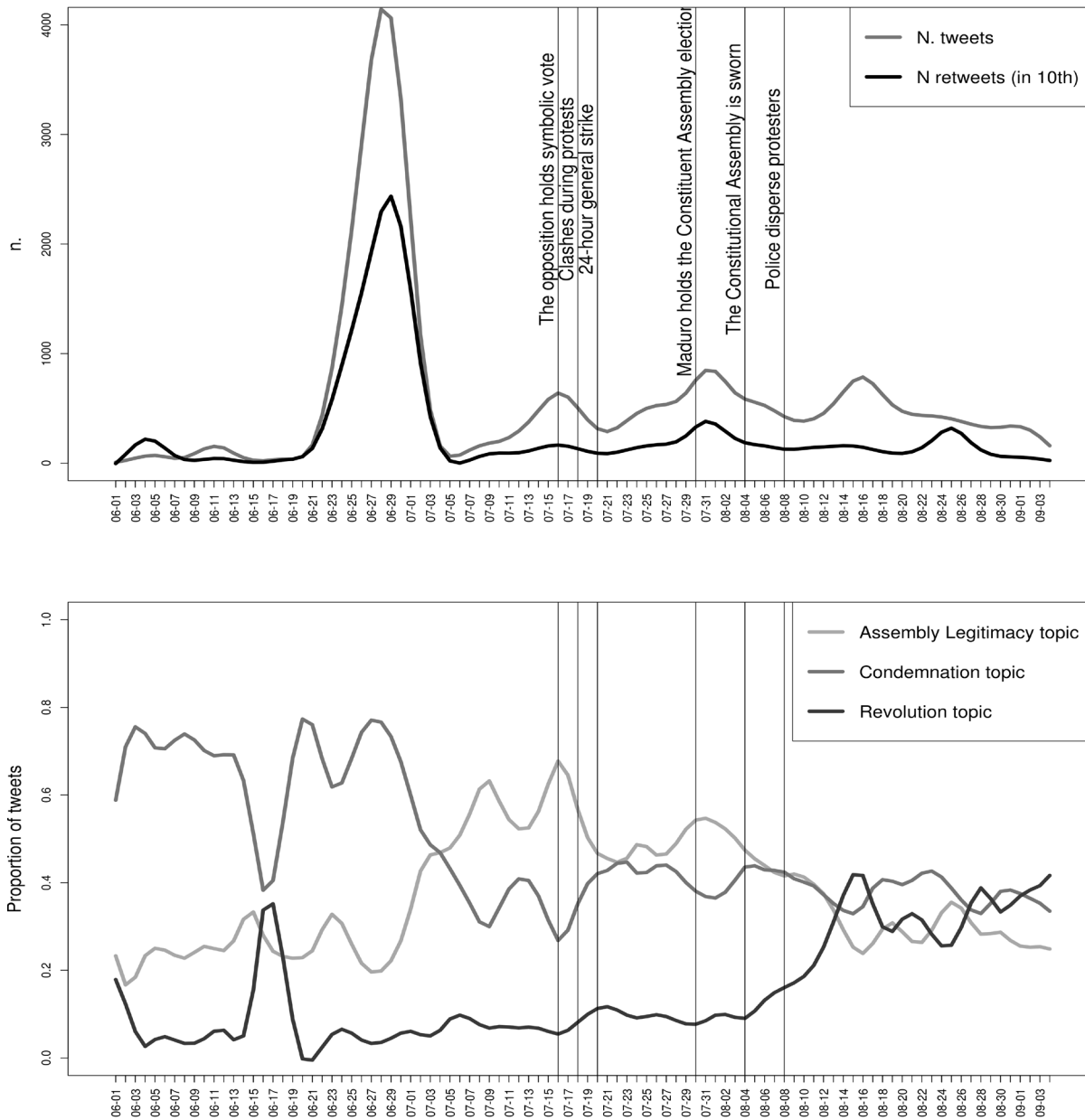
Figure 4. Distribution of the tweets across time as total volume (top figure) and by topic (bottom figure).Note.

The number of retweets is in 10th (so 1 corresponds to 10 retweets) dates are shown in the form Month-

Date (so 06-01 is June 1st)

Figure 5. Difference between the standardized distributions of each positions, by topic and across time.